

# Quantifying Uncertainty in Vehicle Simulation Studies

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## ABSTRACT

The design of vehicles, particularly hybrid and other advanced technology vehicles, is typically complex and benefits from systems engineering processes. Vehicle modeling and simulation have become increasingly important system design tools to improve the accuracy, repeatability, and flexibility of the design process. In developing vehicle computational models and simulation, there is an inevitable compromise between the level of detail and the development/computational cost. The tradeoff is specific to the requirements of each vehicle design effort. The assumptions and detail limitations used for vehicle simulations lead to a varying degree of result uncertainty for each design effort. This paper provides a literature review to investigate the state of the art vehicle simulation methods, and quantifies the uncertainty associated with components that are commonly allocated uncertainty. By understanding the inaccuracies and inconsistencies within these studies, improved simulation methods can be proposed. The consequences or accuracy of common assumptions are determined which will aid future simulation efforts as well as provide metrics for evaluating the appropriateness of past efforts. The results of this paper will aid future simulation design efforts and can begin to define standards by which simulation design studies are conducted.

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## INTRODUCTION

Computational modeling continues to play an increasing role in the automotive design, development, and evaluation process. As vehicle technologies advance at a quick rate, researchers and manufacturers are challenged with not only keeping up with the state of the art, but also predicting and allowing for future design implementations. Computer based simulation plays an important role in supporting advancement of vehicle technology by assisting in systems engineering design processes. As the level of detail included in vehicle models increases, so does the accuracy of the results; but commonly at the cost of increased computational or system development time.

Many modeling tools have been used to simulate a wide range of vehicle types, technologies, and operational characteristics. Different objectives of these simulations can support different levels of detail and therefore acceptable uncertainty in the results. It is a requirement of the simulation end-user to account for the uncertainty that exists within the systems considered and to understand how uncertainty will contribute to the conclusions of any particular study. Simulations are commonly designed to represent a specific functional characteristic of the vehicles well, but can commonly be misconstrued to represent a wider range of

operations than originally intended or validated. As these simulation tools continue to see more use in the academic and industrial automotive design world, they are subjected to more rigorous considerations and applications. The demand for high level details is pushed by an increase in systems engineering design methods that rely heavily on long design explorations through computational based models.

Uncertainty exists in all simulations. The magnitude of this uncertainty must be considered in comparison to the breadth of the results. A number of steps can be taken to evaluate an appropriate method for defining the uncertainty and associating it correctly to the simulation outcomes. The first step in determining uncertainty in a simulation is to classify the type of study being performed. From the type of study performed, objective outputs should be defined. The combination of study and objective type guides the study towards a set of simulation tools that have been specifically designed for that application (whether they exist or not). The second step of determining uncertainty is to define the systems under consideration and their respective data flows (inputs and outputs). The third step requires a detailed evaluation of the equations, assumptions, and parameters implemented in the simulation. The final step requires a validation of the system relative to the type of system and study originally defined. Only after each of these steps have

been completed by the simulation developer and approved by the simulation user can the uncertainty of the vehicle simulation be accurately quantified. Each of these steps will be discussed in further detail in the following sections.

## PURPOSE OF DESIGN STUDIES

The first step in evaluating uncertainty in vehicle simulation studies is to determine the type of study being performed. The type of study can most easily be classified based on its purpose. Within each of the study types, a different set of considerations must be applied to the uncertainty characteristics. Simulation studies can be classified into three main types:

- 1). Technical rankings
- 2). Representations of futures
- 3). System development and exploration

As a subset of each of the three simulations types listed, simulations studies can be performed based on optimization techniques, design of experiments (DoE) parametric methods, or fixed-point formulations [1]. Optimization techniques can include a variety of algorithms ranging from linear programming to stochastic algorithms [2, 3]. Optimizations commonly define an objective and perform simulation iterations to approach the objective within a specified set of solution requirements. DoE parametric methods operate as design space examination approaches that provide a uniform evaluation of a specified range of parameters, inputs, or assumptions. Optimizations commonly differ from DoE studies as the number of simulation iterations increases, wherein optimizations continuously focus their design explorations and DoE studies remain consistently distributed. Fixed-point formulation studies rely on one or a few pre-determined design space points and usually include much fewer simulation iterations. Fixed-point studies most commonly apply to simulation of a pre-specified system with no design exploration.

Technical ranking (TR) studies consist of simulation efforts aiming to evaluate vehicle options in relation to one another. One or many objective evaluation metrics such as fuel economy, system efficiency, total cost of ownership (TCO), or greenhouse gas emissions (GHG), have commonly been used in previous vehicle simulation studies. As with each of the three study types, TR can be performed as an optimization, DoE, or fixed-point study. Optimization TR studies consist of multiple independent optimization of systems such that optimal designs in different categories can be compared. DoE TR studies are performed similarly to optimization TR studies but with a more generalized design space consideration. Fixed-point TR studies intend to compare specific vehicle components or designs such as comparing a specific conventional gasoline vehicle with its matching hybrid model. The TR studies can be particularly sensitive to parameter value specifications but less sensitive to model structure. Details of these sensitivities and sources of uncertainty will be discussed in later sections.

Representations of futures (RoF) studies intend to provide predictions of future technology. These studies can exist in a variety of subsets including economic feasibility, technology limits, technology goals, policy fulfillment, and environmental and social interaction to name a few [4, 5]. RoF studies rely heavily on time sensitive predictions that are proposed to represent a projected future scenario. This type of study usually exists with an initial base simulation for the state of the art (SoA) technology and extends to a future time. Validation of RoF study can only accurately be performed as time progresses, but are commonly tested based on historical cases. RoF studies are asserted to be most sensitive to uncertainty in the assumptions made about future scenarios and definition of the technology SoA.

System development and exploration (SDE) studies aim to investigate the function of the vehicle or its subsystems. SDE studies can include such factors as controller development strategies, component design specifications, trade-off analysis, and scenario implementation. The scenario implementation discussed in the SDE section differs from scenarios from the RoF section as SDE scenarios are based on an available operational environment test case (i.e. different drive cycles) and RoF scenarios are based in a future condition. SDE studies can commonly be associated with Hardware in the Loop (HIL) development and testing. Model structure, including levels or detail, and equation specification, are much more sensitive sources of uncertainty for SDE studies than in the other two study types discussed.

## SIMULATION TOOLS

Simulation studies can be performed using a number of commercially available and custom vehicle simulation tools. In most cases, each specific tool has been created with the intent of fulfilling a design study type need, but there are alternative options for combining multiple tools or developing a custom tool to meet study specifications. The methods used to develop different simulation tools differ in many ways including numerical solvers, direction of information flow, level or detail, organizational structure, and simulated system type. A few of the available simulation tools available as well as their background formulations are detailed in this section.

A multitude of simulation tools are currently available for design studies. One of the primary differences between these tools is the direction of information flow, or causality. Simulations for vehicles can exist in three configurations: forward facing, backward facing, or non-causal (acausal). All three of these simulation types operate in a time progressive manner, the direction of information flow refers to data within the model.

Forward facing simulations of vehicle systems refers to a model where controls and operation of the subsystems operate in a time-progressive feedback manner. For example, a forward facing vehicle simulation of an electric vehicle driving on a dynamometer schedule would follow the

information path shown in [Figure 1](#). A dynamometer drive cycle velocity demand is fed to a system driver that provides a desired torque or throttle demand to the controller. The controller evaluates system limits and transmits the driver demand to the propulsion unit. The propulsion unit supplies tractive effort based on its limited operating conditions as well as calculation of resource/energy use. The resulting vehicle velocity is fed back to the driver and deviations can be accounted for in future commands. Forward facing simulations are generally representative of physical vehicle control systems, and are commonly used for controls development and HIL testing.

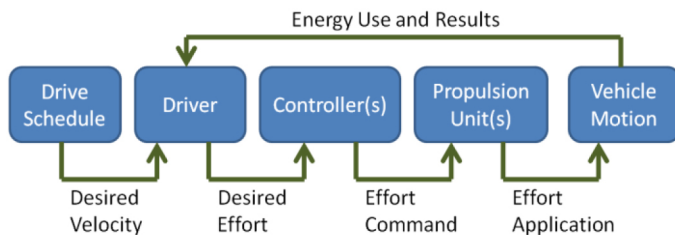


**Figure 1. Forward facing simulation flow diagram**

Backward facing simulations of vehicles have a similar general structure as forward facing simulations, but with different information flows. In backward facing simulations, shown in [Figure 2](#), it is assumed that a propulsive unit meets drive commands, and energy use can be calculated from the required tractive effort. Backward facing simulations are typically less computationally expensive than forward facing simulations due to a lack of information feedback and complex controls. It is more difficult for backward facing simulations to calculate maximum vehicle performance, such as maximum acceleration, because the simulations are not designed to predict operation of the components at their limits.

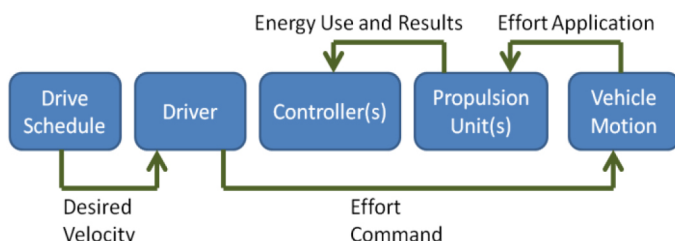


**Figure 2. Backward facing simulation flow diagram**

Non-causal simulations use a combination of forward and backward facing causality information flow. In some systems this can be implemented through switching calculation type. For example switching information can occur when a backward facing simulation reaches an event in the vehicle simulation where a required component operation is unavailable (e.g. a motor reaches its peak torque). In this case the drive cycle may not be met and continued simulation will require additional controller functionality to get the vehicle

operation back on track - which occurs in a forward facing manner until normal operation resumes. An alternative non-causal simulation tool may have a combination of forward and backward facing calculations simultaneously. For example, controllers send commands in a causal information direction, but power flows through an epicyclical gear (planetary) in multiple directions.

Each of the simulation tools available differs in calculation methods and considerations. [Table 1](#) provides a compiled list of some of the simulation tools, the developer of the simulations, and a little information about the simulation methods. Tools should be selected depending on the type of simulation being performed. Additional aspects of each of the simulation tools and how they relate to the uncertainty of the vehicle simulations will be described in later sections.

## TYPES OF UNCERTAINTY

Uncertainty has classically been defined in many different ways depending on the systems that provide and measure the uncertainty [23]. The primary focus of this section is to understand the uncertainty that exists in vehicle simulations studies. Vehicle simulation studies most directly relate to uncertainties in simulation and computation methods, data acquisition from physical systems, and equation formulation. Secondary sources of uncertainty such as environmental random conditions, human error, and future forecasting must also be included but interact with the system at a higher level and can be ignored for some studies.

Uncertainty in vehicle simulations has been classified into three groups [12]:

- 1). Type-1 uncertainty: Variability of input or parameters. Type-1 uncertainty is usually handled by providing distribution functions of the defined inputs and parameters when available.
- 2). Type-2 uncertainty: Similar to Type-1 uncertainty where variability exists in the inputs and parameters but without a known distribution. Fuzzy logic and evidence theory have been used for solutions.
- 3). Type-3 uncertainty: Uncertainty from an unknown process. This type of uncertainty is the most difficult to find solutions for.

Uncertainty can also be classified as either aleatory or epistemic [23]. Aleatory uncertainty pertains to information that can be represented by a distribution; epistemic refers to completely unknown factors. Type-1 uncertainty can be classified as aleatory, Type-3 uncertainty can be classified as epistemic, with enough testing it is likely that Type-2 uncertainty can also be described using a distribution of data; classifying it in the aleatory uncertainty.

Measuring error and uncertainty should include an understanding of the accuracy and precision of the data sets, wherein accuracy represents the measured difference between a predicted and measured value, precision compares the

**Table 1. Comparison of simulation tools**

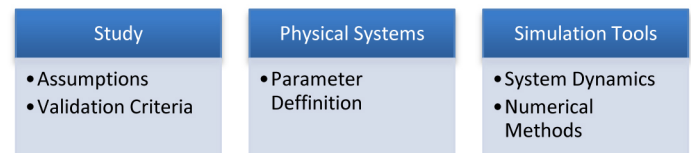
| Program Name               | Developer                                    | Notes                                    |
|----------------------------|----------------------------------------------|------------------------------------------|
| ADVISOR [6, 7, 8, 9, 10]   | National Renewable Energy Laboratory (NREL)  | Simulink, Backward facing                |
| ADAMS/CAR [11, 12]         | MSC.Software                                 | Dynamic chassis simulation               |
| Autonomie [13]             | Argonne National Laboratory (ANL)            | Simulink GUI, Essentially a newer PSAT   |
| CAR [10]                   | West Virginia University                     | Four architectures, Dynamic, Matlab      |
| CarSim [8, 10]             | AeroVironment, Inc.                          | Vehicle Dynamics, Chassis, Animations    |
| COOOL [1]                  | Colorado School of Mines                     | Object-oriented optimization library     |
| CRUISE, BOOST, etc [14]    | Anstalt für Verbrennungskraftmaschinen (AVL) | Dynamic, Matlab Interface                |
| CSM HEV [1, 8, 10]         | Colorado School of Mines                     | Simulink                                 |
| Dymola [2]                 | Dassault Systems                             | Modelica based vehicle models            |
| EPA MOVES [15]             | Environmental Protection Agency (EPA)        | Emissions Simulation, Java, MySQL        |
| FASTSim [16]               | National Renewable Energy Laboratory (NREL)  | Excel, lumped parameter                  |
| HEVsim                     | Wayne State University                       | Backwards-facing, iterative, LabVIEW     |
| HEVSIM [17]                | Wuhan University of Technology               | Simulink, Forward facing                 |
| HEV V-Elph [18, 8, 10]     | Texas A & M University                       | Simulink, Dynamic                        |
| HVEC [8, 19]               | Lawrence Livermore National Laboratory       | EV and Series Hybrids                    |
| LabVIEW                    | National Instruments                         | Dynamic ODE solver                       |
| LFM [2]                    | Electric Power Research Institute            | Simulink, developed vehicle library      |
| Matlab/Simulink Custom [7] | Mathworks                                    | Causal, Dynamic or fixed step            |
| Modelica [2]               | The Modelica Association                     | Non-causal, dynamic PDE, object oriented |
| PAMVEC [20]                | Dr. A. Simpson                               | Excel, Lumped parameter                  |
| Powell [21]                | B. K. Powell, Ford Motor Company             | Quasi-static custom model                |
| PSAT [1, 20]               | Argonne National Laboratory (ANL)            | Simulink GUI, Forward Facing             |
| SIMPLEV [8, 10]            | Idaho National Laboratory (INL)              | Simulink, Static Maps                    |
| Virtual Test Bed [22]      | University of South Carolina                 | Highly dynamic computation               |

distribution of the predicted and measured values. Models and simulations can be accurate without being precise or vice-versa. The measures of accuracy and precision can aid in identifying the sources of uncertainty. For example, an inaccurate but precise simulation may account for input distributions well, but use a parameter value that deviates from the value that should be used.

Control and dynamic systems define uncertainty by a difference between models and reality [23]. Error is the measure of the difference between some observed value and its prediction from a model or simulation. The uncertainty of simulations can be determined through combining the input parameter distributions, validation error, numerical approximations, and the other uncertainty types as presented in the following sections of this paper.

## SOURCES OF UNCERTAINTY

Uncertainty in vehicle simulation studies usually occurs from multiple sources. It is the responsibility of researchers to identify the primary sources of uncertainty in the simulation methods they are using and ensure that the uncertainty is properly accounted for in the simulation and results. A few of the identifiable sources of uncertainty include: system dynamics, numerical methods, parameters, assumptions, and validation criteria [24]. These five sources of uncertainty each fit into different portions of a simulation study as shown in Figure 3.

**Figure 3. Sources of uncertainty in vehicle simulation.**

## SYSTEM DYNAMICS UNCERTAINTY

Real world systems are highly dynamic. As these systems are modeled in a computational domain considerations must be made as to the frequency of solving different system equations. Continuous time step and fixed time step computational solvers have been used in vehicle simulation studies and will be discussed in more detail. Before selecting which solver should be used, an understanding of the rate of variable change in dynamic systems must be considered.

In the real world, changes in systems occur at an infinitesimally small time scale. A common way of considering these systems is to make measurements of the systems based on common unit measurements. For example, even though ambient temperature can be measured to as many significant figures as the measurement device allows, for vehicle systems only two significant figures are commonly used because the performance of most automotive systems is insensitive to small changes in temperature. This means that the computation of the ambient temperature in a vehicle system simulation only needs to occur such that changes can be accounted for at the specified level of detail.